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Spatio-Temporal Evaluation of Urban Growth of Zuru Metropolis, Nigeria

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ABSTRACT

The pattern of development in a city is mostly governed by urban dynamics, with population increase being the primary driving force. Built-up cover is the most important predictor of urban expansion. Zuru metropolis in Kebbi State has witnessed remarkable developmental activities caused by human influences such as buildings, road constructions, and population growth for over decades. Urban growth was ascertained for a period of 30 years through the analysis of Landsat imagery of 1988, 1998, 2008 and 2018. The datasets were classified into five (5) land covers, namely, built-up, water body, rocky surface, vegetation, and others. Quantitative assessment of the urban growth was ascertained by computing post-classification LC dynamics and Land Consumption Rate/Land Absorption Coefficient (LCR/LAC). The results showed that the built-up cover (urban area) conspicuously increased with area of 693.35 ha, 728.74 ha, 5210.5 ha and 6845.75 ha respectively for the period of study (1988 - 2018). The increment in built-up area was indicative of population growth from 1988 to 2018. The study revealed that between 1988 to 2018 showed that built-up increased by 11.78%, while rocky surface and water body have shrunk by 16.44% and 0.02% respectively, which can be attributed to anthropogenic activities in which rocky surface and waterbody have been transformed into built-up cover. It further revealed that the urban area experienced crowdedness in the years 2008 and 2018 respectively due to high LCR values of 2.71% compared to LCR values of 0.0714% and 0.0558% in 1988 and 1998. Land transformation into urban area and spread of the population to the outskirts of the study area was prominent between 1998 and 2008 due to high LAC value of 0.0998. The study concluded that there was transformation of rocky surface and waterbody into urban area, which was caused by population growth, human and agricultural activities in Zuru metropolis.

Keywords: Built-up, Change detection, Land Absorption Coefficient, Land Coefficient Ratio, Urban growth

1.0. Introduction

Conspicuous transformation of the lithosphere, due to both natural and manmade influences, which is connected to man's drive to expand his shelter, has been evident in the 21st century (Foley *et al.*, 2005). Urban growth is related to landscape transformation (Forman, 1995). Although these two processes are completely similar, urban growth defines growth from non-urban to an urban area, whereas landscape transformation defines types of fragmentation, such as reductions of non-urban areas (Viana *et al.*, 2019). Urban growth is a spatial and demographic process and refers to the increased importance of towns and cities as a concentration of population within a particular economy and society (Bhatta, 2010). Therefore, the motif of LULC reflects the arrangement or spatial scattering of the built environment (Viana *et al.*, 2019).

Outlying growth is distinguished by a transition from non-urban to urban land use that happens away from existing urban districts. In isolated growth, one or more non-urban regions are urbanized at a distance from existing urban centers. This sort of growth is typical of a new house or a similar construction, surrounded by little or no urban space (Wilson *et al*., 2003). The indicators of urban growth are land use and land cover (LULC). The LULC serves as a tool for quantitatively measuring urban growth overtime. Land use as defined by Ololade *et al.* (2008) is the manner in which human beings employ the land and its resources. Land covers are the regular contributors of the physical condition of the ground surface (Jeevalakshmi *et al*., 2016). Land cover refers to features of land surface, which may be natural, semi-natural, managed, or manmade (Bhatta, 2010).

Changes in land cover, according to many academics, have become a key issue in the broader discussion of global warming; and that change originates from human-induced influences on the environment and their implications for climate change (Lambin *et al.,* 2001; Woldeamlak, 2002; Ginblett, 2006). Detection of LC changes is the process of identifying differences in the state of an area or region by analyzing images acquired on different dates (Singh, 1989; Ololade *et al*., 2008). Various cities in Nigeria have seen a significant shift in land cover, which has been mostly affected by humans. This is due to urban migration as a result of population increase, growing poverty, and a high percentage of unemployment. Abbas and Iguisi (2008) reported that the growth of agricultural activities and urbanization are the predominant and proximate causes of land use and land cover change activities in Nigeria. Similarly, this is not an exception in Zuru and its surroundings, which have large-scale agricultural (Bello *et al*., 2014).

In recent years, remotely sensed (RS) technology has been used in the monitoring of LULC, with encouraging results. The RS technology has evolved into an essential tool for stakeholders to use in evaluating and anticipating LULC as it occurs throughout time (Aliyu *et al*., 2020). Previous studies have used remotely sensed datasets to assess land cover over time in various developing countries across the world (Rimal *et al.,* 2020). Some of the studies addressed: analysis of LULC changes (Mmom and Fred-Nwagu, 2013; Bello *et al*., 2014; Mishra *et al*., 2014); analysis of LC changes (Bakr *et al*., 2010; Abiodun *et al*., 2011; Fichera *et al*., 2012); change detection of urban sprawl (Oyinloye, 2010; Tamilenthi and Baskaran, 2011; Viana *et al*., 2019); monitoring and forecasting of spatio-temporal LULC using CA Markov (Yikalo, 2009; Sundara Kumar *et al*., 2015; Aliyu *et al*., 2020).

In an earlier study of the land use-land cover changes of Zuru and its environment by Bello *et al*. (2014), a period of twenty-two (22) years was analyzed using Landsat 5 (TM) imageries of 1986, 1999 and Landsat 7 (ETM+) imagery of 2008 in ILWIS software. It is more than a decade between the year 2008, when the aforementioned study was done, and the year 2018. Therefore, Zuru local government area has witnessed remarkable expansion, growth and developmental activities such as building, road construction, deforestation and many other anthropogenic activities just like many other local government headquarters in Nigeria. This has further resulted in increased land consumption and a modification and alterations in the status of her land cover over time. It is therefore, necessary for a study such as this to be carried out if Zuru was to avoid the associated problems of a growing and expanding urban area like many others in the world.

It is against this fact that this study aimed at carrying out spatio-temporal evaluation and forecasting of urban growth of Zuru Metropolis, Nigeria to locate specific growth of built-up areas and other land covers. The aim was achieved through these objectives, namely: 1) derive land cover maps of the area for 1988, 1998, 2008 and 2018); and 2) quantify land cover change metrics from the generated maps. This current study covered the whole of Zuru LGA, which is 52ha as opposed to 36.36 km^2 that was studied by Bello *et al*. (2014). This study analyzed the LC of Zuru for four (4) epochs at 10 years interval, over a period 30 years. Therefore, this study improved upon the work of Bello *et al*. (2014). However, the major limitation encountered was the acquisition of Landsat 7 with much cloud as it could introduce mixed colors into the image maps. The findings of the study can be applied for planning and development of Zuru metropolis.

2.0. Methodology

2.1. Study area description

Zuru local government area (LGA) is located in the South Eastern region of Kebbi State Nigeria with a total land mass of 52.153.92 ha. It lies between longitude 4° 27' 0"E to longitude 6° 00’ 00” E of the central meridian and latitude 10° 50’ 24” N to Latitude 11° 50’ 24” N of the equator and. Zuru is bounded in the West by Gwandu and Yauri while in the East it shares boarder with Kuyanbana. It has a population of about 165,335 as at 2006 (NPC, 2006).

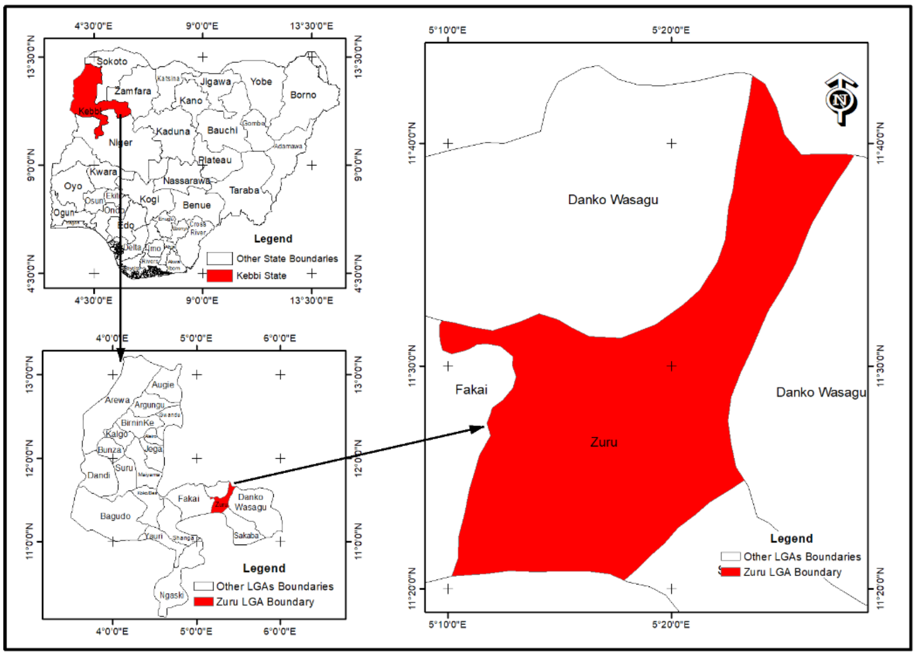

Figure 1: Inset map of the study area

2.2. Methods

The techniques used for the study, which cut across data collection, processing and analysis of the land covers is shown in Figure 1.

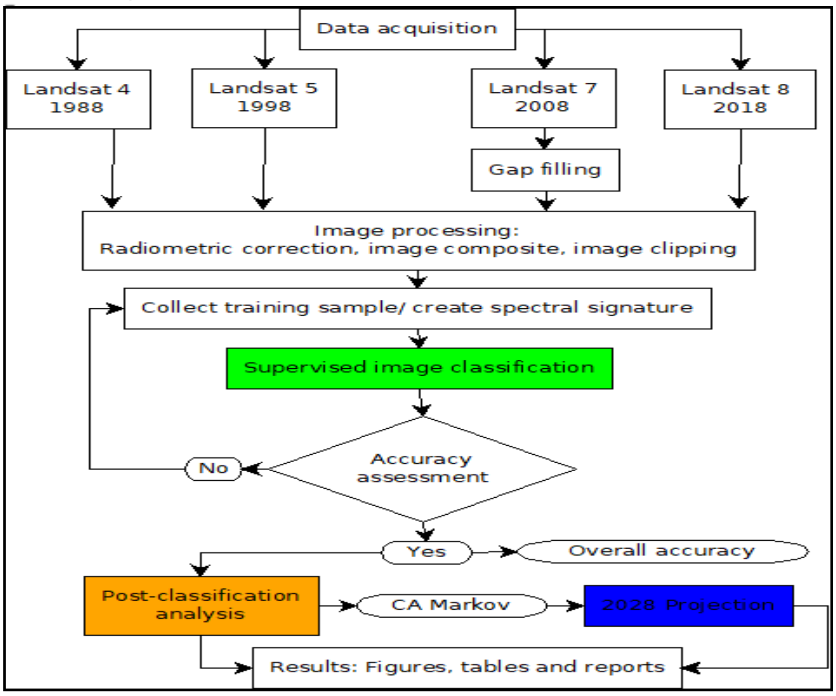

Figure 2: Workflow diagram of the study

2.3. Datasets and sources

Near anniversary (November and January) multispectral optical remotely sensed datasets were acquired having path/row of 190/52. The images were acquired in the dry season to avoid dense vegetation. The images were registered to Projected Coordinate System WGS 84, UTM Zone-31N. The images were cloud-free except for the Landsat 8. The details of the various datasets and their sources are shown in Table 1.

Table 1: Datasets and their Characteristics

S/N	Data Type	Date	Resolution /Scale	Source	Purpose
1.	Landsat 4 TM	29/01/1988	30m	http://www.glovis.usgs.gov	Land cover classification
2.	Landsat 5 TM	16/11/1998	30m	http://www.glovis.usgs.gov	Land cover classification
3.	Landsat 7 ETM+	13/01/2008	30m	http://www.glovis.usgs.gov	Land cover classification
4.	Landsat 8 OLI	07/01/2018	30m	http://www.glovis.usgs.gov	Land cover classification
5.	Google Earth Pro	02/01/2018	1m	http://www.googleearth.com	Visual interpretation
6.	Administrative map	05/08/2018	-----	http://www.gadm.org	Extraction of study area

2.4. Data processing

Scan line correction of Landsat 7 ETM+
The scan gaps in the Landsat 7 images were filled appropriately using the histogram matching method in ENVI v5.1.

Radiometric correction
Radiometric correction was applied to the Landsat images. The level of the correction was from digital number (raw) to at-sensor spectral radiance. This was to compensate for the difference in acquisition time and date of the sensors. Conversion to surface reflectance was not carried out since surface materials were not generated for this study such as indices. The algorithms for the radiometric correction are shown in Equations 1 and 2.

1. Conversion of DN to radiance (for TM and ETM+)

$$L_\lambda = \frac{L_{MAX\lambda} - L_{\mathrm{MIN\lambda}}}{Q_{\mathrm{calmax}} - Q_{\mathrm{calmin}}} (\mathrm{Q_{CAL}} - \mathrm{Q_{CALMIN}}) + \mathrm{L_{MIN\lambda}}) \tag{1}$$

2. Conversion of DN to Radiance (for OLI and TIRS)

$$L_\lambda = M_L \times Q_{cal} + A_L \tag{2}$$

where:

L_λ	Spectral radiance at the sensor's aperture
Q_{CAL}	Quantized calibrated pixel value (DN)
Q_{calmin}	Maximum quantized pixel value (corresponding to $L_{MAX\lambda}$) in DN = 255
$L_{MIN\lambda}$	Spectral radiance that is scaled to Q_{calmax} (W. m-1. ster-1. µm-1)
$L_{MAX\lambda}$	Spectral radiance that is scale to Q_{calmin} (W. m-1. ster-1. µm-1)
M_L	Band-specific multiplicative rescaling factor from the metadata (RADIANCE_MULT_BAND_x, where *x* is the band number).
A_L	Band-specific additive rescaling factor from the metadata (RADIANCE_MULT_BAND_x, where *x* is the band number) (LSDS, 2019). This operation was carried out in ENVI v5.1.

Image composite and clipping
For the Landsat TM and ETM+ images, band 1, 2, 3, 4, 5 and 7. Also, band 2, 3, 4, 5, 6, and 7 were stacked for Landsat 8 for color renditions. Then clipping was carried out using the boundary shapefile in ArcMap v10.5.

2.5. Data analysis

Pixel-based image classification

Here, varying numbers of training samples were collected from the images and converted into spectral signatures. Then, supervised image classification was carried out on the images and the Maximum Likelihood Classifier (MLC) was used as a parametric decision rule. It assumes (Ongsomwang, 2007) that the probabilities are equal for all classes and that the input bands have normal distribution. However, the drawback of the MLC is that when low-spatial resolution satellite image is used, and especially, if mixel (mixed pixel) exist in the image, there would be a possibility of overlapping of probability distribution in the feature space. Thus, a high classification accuracy cannot be always expected for a low-resolution satellite image (Susaki and Shibasaki, 2000). The Landsat images were classified into five (5) classes, namely: built-up, waterbody, rocky surface, vegetated land and others (all other land use and land cover not included in any of the classes described). They were based on the Anderson LULC classification system (Anderson *et al*., 1976).

Accuracy assessment

The accuracy assessment was computed for the classified images to evaluate the degree of misclassification among LCs due to omission and commission. A total of 50 sample points were generated for each image in a stratified random sampling manner to generate error matrices. The idea here was to have ten (10) sample points for each class since there were five (5) land cover classes identified for the study.

Change detection analysis

Change detection analysis was performed for the five LC classes at intervals: 1988–1998, 1998–2008, 2008-2018 and 1988–2018 respectively. Four (4) LC change maps were outputted to display the change of the classified images. The change detection statistics was computed using the Module for Land Use Simulation Change Evaluation (MOLUSCE) plug-in in qGIS v10.1 software. The change analysis was both quantitative and graphical. It computed the land cover area, change in area and area percentage.

Land absorption coefficient/land consumption rate

LCR is a measure of compactness that reflects a city's progressive spatial growth. When the value of LCR is high, it indicates crowdedness and if the value is low, it indicates free spaces. Whereas LAC is a measure of how much additional urban land is consumed for each unit growth in population. It shows how fresh land is being exploited for development and how the population is spreading to the periphery or sprawling (Laxmikant *et al*., 2012).

It requires land area of the city (built-up) in hectares and the corresponding population size, for the respective years of interest (Aliyu *et al*., 2020). The estimated built-up area was obtained from the classified maps (Figure 4). The calculations were based on the assumption that land consumption grows with population growth, resulting in increased urban expansion (Laxmikant *et al*., 2012). The mathematical expressions for the LAC and LCR are shown in Equations 3 and 4 (Yeates and Garner, 1976):

$$\mathrm{L(ha)} = \frac{\mathrm{CityExtensionHectares\ (A)}}{\mathrm{Population\ (P)}} \tag{3}$$

$$\mathrm{L(ha)} = \frac{\text{Extent for the recent year } (\mathrm{A}_2) - \text{Extent for the early year } (\mathrm{A}_1)}{\text{Population for the recent year } (\mathrm{P}_2) - \text{Population for the early year } (\mathrm{P}_1)} \tag{4}$$

The population size was estimated (Parker, 2002) using the projected population expression (Equation 5) with the establishment census data of 2006 and the 3.0% growth rate for the study area.

$$Pop_{(projected)} = Pop_{(known)} \times \left(1 + \frac{AnnualGrowthRate}{100}\right)^{T} \tag{5}$$

where T is time interval between initial year and projected year.

3.0. Results and Discussions

3.1. LC distribution

The LC maps and their area distributions together with percentage equivalent of the area of Zuru from 1988 to 2018 are presented in Figures 3a - 3d and 4. The results showed that the built-up cover (urban area) conspicuously increased with area of 693.35 ha (1.33%), 728.74 ha (1.4%), 5210.5 ha (9.98%) and 6845.75 ha (13.12%) respectively for the period of study (1988 to 2018). The increment in built-up area was indicative of population growth from 1988 to 2018 since the population estimates for the year 1988, 1998, 2008 and 2018 were computed as 97117, 130517, 175404, and 235728, respectively (see Table 4). It was also observed that rocky surface dwindled from 10,567.8 ha (20.25%) in 1988 to 1985.84 (3.81%) in 2018. This decrease could be attributed to either land conversion of the rocky surface into built-up area as a result of search for land for construction on a rocky foundation, or crushing of the rocky surface into granite of various sizes as building materials. The 9.98% area percentage of built-up in 2008 contradicted the 7.76% area percentage of built-up in 2008 of Bello *et al*. (2014). This disparity is due to difference in extent of study considered by both studies. This current study covered an area of 52,186.86 ha (521.868 km^2) while the former considered an area of 36.56 km^2.

Classification accuracy

A confusion matrix was generated by comparing the value assigned during the classification process to the actual value from the satellite images. The matrix showed the user and producer accuracies, the errors of commission and omission, and the overall accuracy and the kappa coefficient. This is presented in Tables 2 and 3. The overall accuracies obtained for 1988, 1998, 2008 and 2018 were 88%, 86%, 86% and 64% respectively. There was 84%, 83%, 82% and 55% statistical agreement (kappa coefficient) between the reference points and the classified maps for 1988, 1998, 2008, 2018. This suggests that the supervised classification was done with the good refinement. However, the 64% and 55% accuracy and kappa values for the LC map of 2018 was due to inevitable cloud cover and mixed-pixels in the image. Thus, it was moderately accurate, which is supported by Onsomgwong (2007) following Jensen (2005) stated that Landis and Koch (1977) concluded that Kappa values between 40% and 80% represent moderate agreement or accuracy.

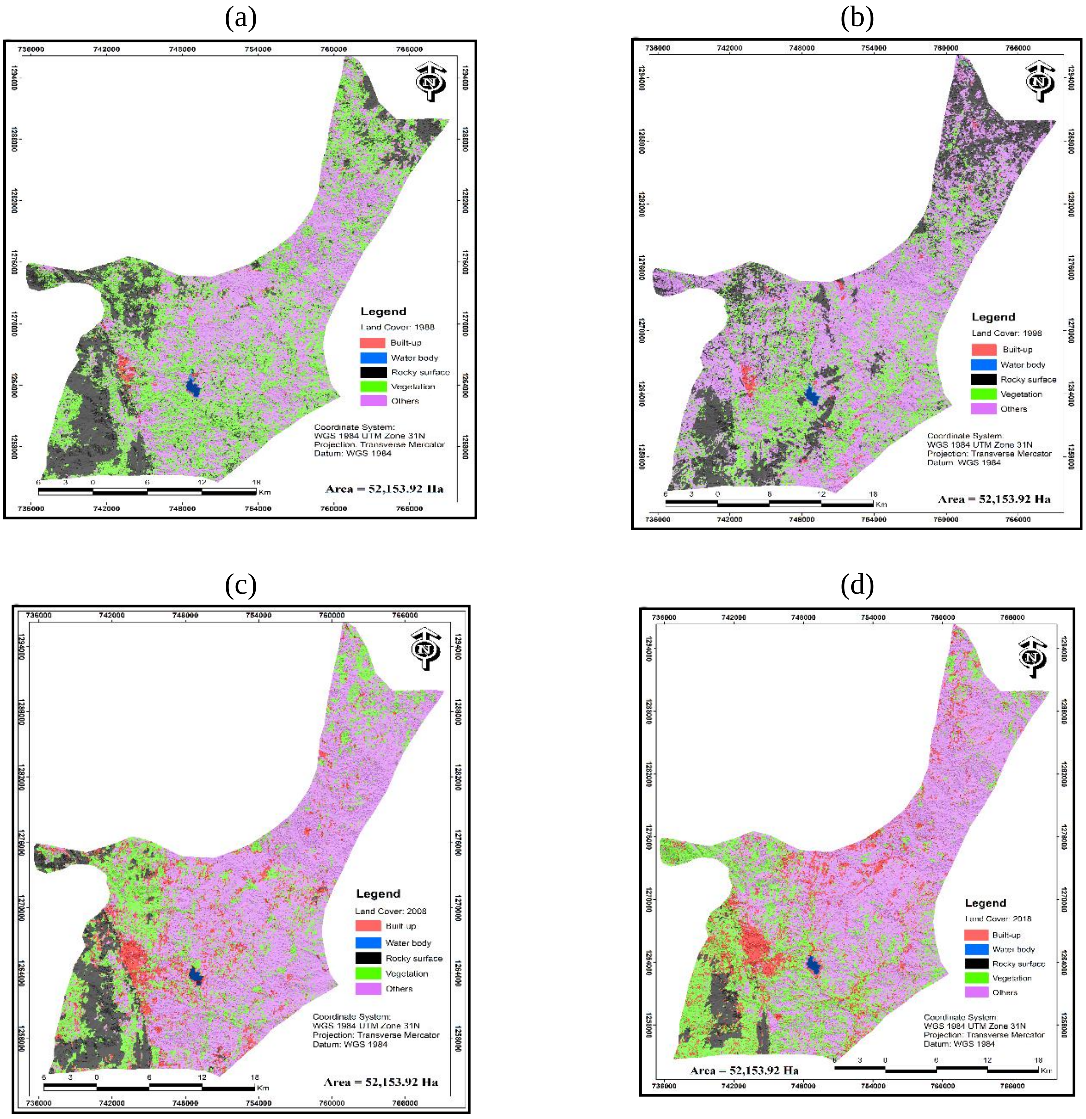

Figure 3: Classified maps of LC in Zuru (a) 1988 (b) 1998 (c) 2008 (d) 2018

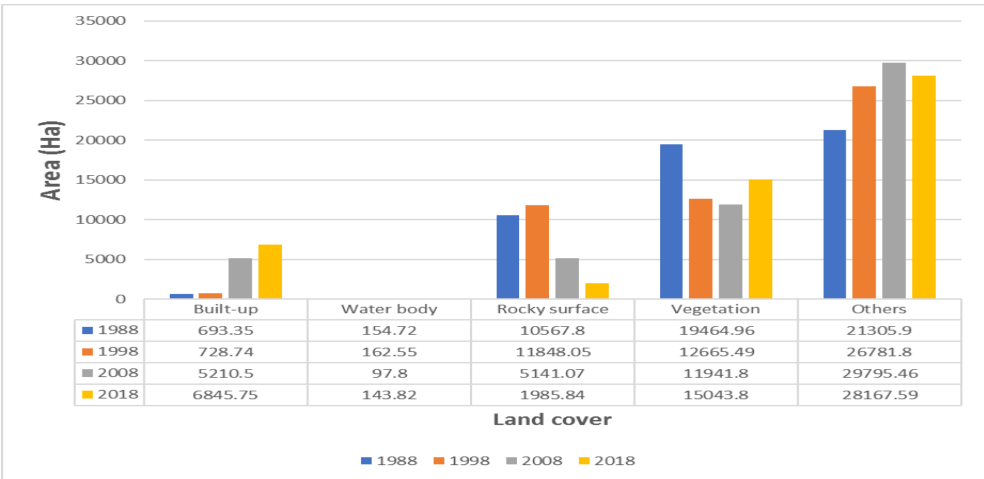

Figure 4: Land cover area for classified image maps of 1988, 1998, 2008 and 2018.

Table 2: Statistics for accuracy assessment of classified LC maps for 1988, 1998, 2008 and 2018

S/N	Class	1988				1998			
		A_1 %	A_2 %	B_1 %	B_2 %	A_1 %	A_2 %	B_1 %	B_2 %
1	Built-up	5.88	34.69	94.12	65.31	12.20	28	87.80	72
2	Water body	8.16	10.00	91.84	90.00	0	5.88	100	94.12
3	Rocky Surface	17.24	4.00	82.76	96.00	22.22	2	77.78	98
4	Vegetation	16.67	10.00	83.33	90.00	2.33	16	97.67	84.
5	Others	11.32	4.08	88.68	95.92	27.27	18.37	72.73	81.63

S/N	Class	2008				2018			
		A_1 %	A_2 %	B_1 %	B_2 %	A_1 %	A_2 %	B_1 %	B_2 %
1	Built-up	33.33	18.37	66.67	81.63	57.81	35.71	42.19	79.59
2	Water body	0	40	100	60	20.41	20.41	79.59	56
3	Rocky Surface	0	8	100	92	24.32	44	75.68	40
4	Vegetation	12.28	0	87.72	100	53.49	60	46.51	77.97
5	Others	16.07	6	83.93	94	19.30	22.03	80.7	64.29

Note: *A1 = Error of Commission; A2 = Error of Omission; B1 = User's Accuracy; B2 = Producer's Accuracy.*

Table 3: Overall accuracy and Kappa coefficient of Classified LC Maps for 1988, 1998, 2008 and 2018

S/No	Year	Overall Accuracy (%)	Kappa coefficient (%)
1	1988	88	84
2	1998	86	83
3	2008	86	82
4	2018	64	55

3.2. Urban growth detection

Figure 5a -5d presents the LC change between successive years. The bar to the right (green) signifies an increase while the bar to the left (red) signified a decrease. The land cover change metrics of Zuru from 1988 to 2018 is shown in Figure 5. It can be observed that the change in built-up area was 35.39 ha between 1988 and 1998, 4481.76 ha between 1988 and 2008, 1635.25 ha between 2008 and 2018, and 6152.41 ha between 1988 and 2018 respectively. This result signified an expansion in urban space of the study area. The built-up area class is the most important predictor of urban area expansion (Aliyu *et al*., 2020). Vegetation and rocky surface classes recorded losses in area change (see Figure 5a -5d) because they were converted and modified into built-up area. This is one of man-made influences on the biophysical cover as he expands his shelter.

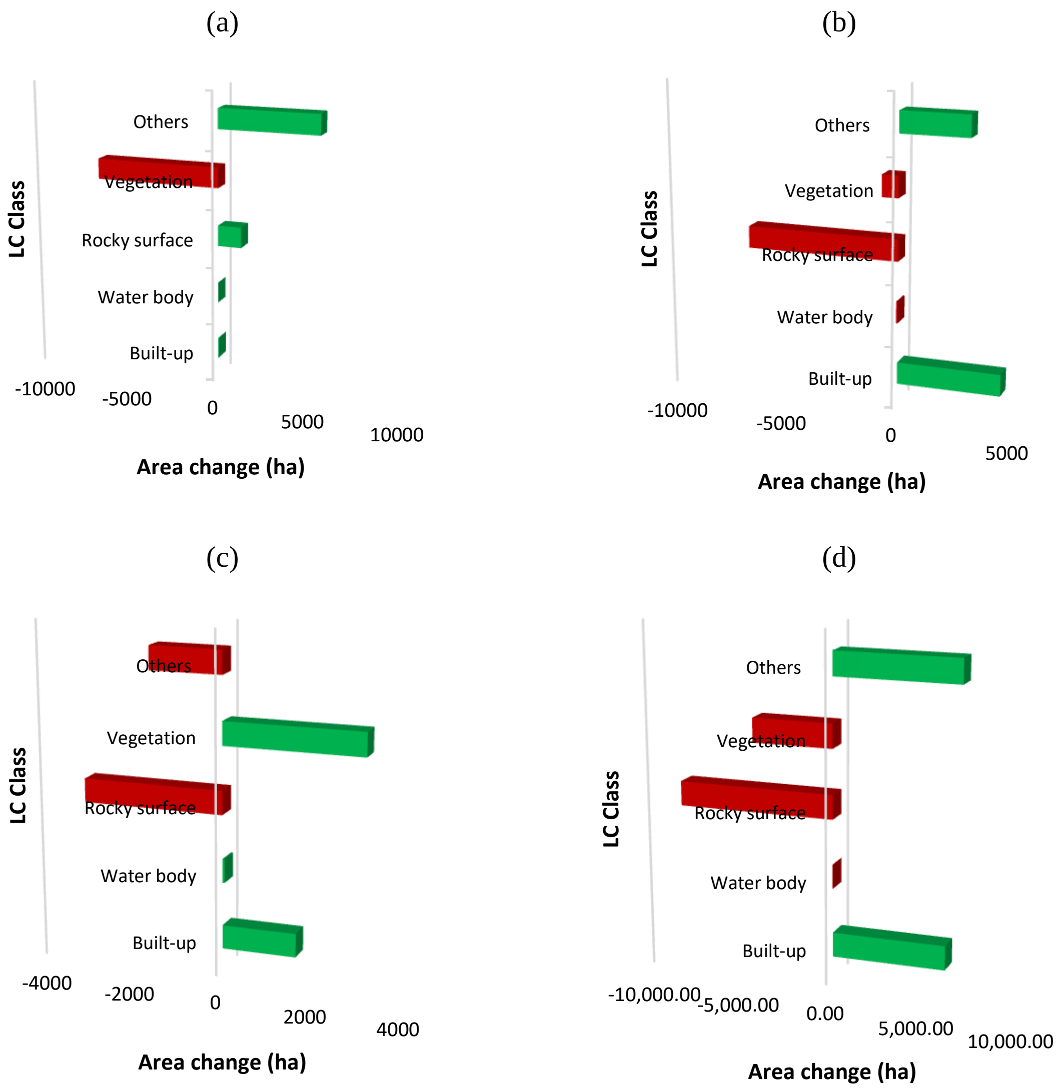

Figure 5: LC Area Change: (a) 1988-1998, (b) 1998-2008, (c) 2008-2018, and (d) 1988-2018.

Land absorption coefficient/land consumption rate

The projected population estimates for the year 1988, 1998, 2008 and 2018 were computed as 97117, 130517, 175404, and 235728, respectively (Table 4). The population figures were interpolated using a growth rate of 3% as reported by the National Population Commission (2010) and the baseline population of 2006. The LCR decreased from 0.71% in 1988 to 0.56% in 1998. It further increased from 1998 to 2.97% in 2008 and 2018 (see Table 4). This signified that there was crowdedness in urban area in 1988 compared to the year 1998. The increase in the LCR in 2008 and 2018 revealed that the crowdedness increased in the years 2008 and 2018 respectively. The pattern of LCR values of this study agreed with that of Laxmikant *et al*. (2012). The increase in LCR values from earlier to recent year of this study agreed with the works of Aliyu *et al*. (2020) and Oloukoi *et al*. (2014).

Furthermore, between 1988 and 1998, the LAC was 0.0011, it was 0.0998 between 1998 and 2008, and it was 0.0271 between 2008 and 2018 as shown in Table 4. This implied that between 1998-2008, new lands were explored for urban development and the population spread to the periphery than between 1988-1998 and 2008-2018. The LAC between 2008-2018 was also higher than between 1988-1998. The overall LAC between 1988-2018 was 0.0444, which was higher than the LAC (0.127) for a period of 1999-2019 for Akure, Ekiti state of Nigeria.as reported by Aliyu *et al*. (2020). Similarly, the LAC of this study was also higher than the LAC (0.013) for a period of 1986-2009 for Ile-Ife city, Osun state of Nigeria as reported by Oloukoi *et al*. (2014).

Table 4: LCR/LAC of the urban area of the period of study

S/No	Year	Area (ha)	Population	LCR (%)	Year	Area change	LAC
1	1988	693.35	97117	0.71	1988-1998	35.39	0.0011
2	1998	728.74	130517	0.56	1998-2008	4481.76	0.0998
3	2008	5210.5	175404	2.97	2008-2018	1635.25	0.0271
4	2018	6845.75	235728	2.90	1988-2018	6,152.41	0.0444

4.0. Conclusions

This study evaluated the urban growth of Zuru LGA of Kebbi state, Nigeria in space and time. The datasets used for the evaluation were acquired for three decades (1988-2018). The LC distribution was determined for the established objectives. The study revealed that built-up (urban) area increased based on the percentage equivalent of area of 1.33%, 1.4%, 9.98% and 13.12% for the 1988, 1998, 2008 and 2018 respectively. This increment was detrimental majorly to the vegetation cover. From the findings, it revealed that Zuru is characterized by rock-outcrop, which was modified to urban area because of the reduction in size of the rock-outcrop being taken by the built-up area. The studied LULC results showed that the net change for the built-up area, waterbody, rocky surface, vegetation and others over the study period (1988–2018) to be +6152.41ha, -10.90ha, -8582.05ha, -4421.07ha and +40.82ha respectively. The study established that the increment in urban area is commensurate to the rise in population growth. The LCR and LAC analyses revealed that there was crowdedness in the urban area in 2008 and 2018 as population increased. The LAC had it that between 1998-2008, new lands were sought for urban expansion. The findings of this study would serve as tool to decision-makers in the management of land resources in the study area. It would also aid in visual communications during policy making. It was suggested based on the results of the study that the planning urban authority should develop urban planning measures by providing short-term and long-term planning since urban area has expanded and is distributed over the study area. This would ensure that vegetation and other covers are not converted and modified into urban area indiscriminately. Further studies should be conducted in the study area for periodic investigation of the urban growth.
Furthermore, it should be noted that socio-economic and climatic drivers of land cover to urban area were not accounted for in the study due to the unavailability of the datasets. However, the algorithms used for the study were within the acceptable results as compared to related studies.

Conflict of Interest
There is no conflict of interest among the authors.

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